PCT/DK 00/00310

DK 00/310

REC'D 12 JUL 2000

WIPO PCT

4

Kongeriget Danmark

Patent application No.: PA 1999 01503

Date of filing: 20 October 1999

Applicant: NOVI Innovation A/S
Niels Jernesvej 10
DK-9220 Aalborg Ø

This is to certify the correctness of the following information:

The attached photocopy is a true copy of the following document:

- The specification as filed with the application on the filing date indicated above.

Patent- og Varemærkestyrelsen • Kongeriget Danmark

Patent- og
Varemærkestyrelsen
Erhvervsministeriet

TAASTRUP 27 June 2000

Lizzi Vester

Lizzi Vester
Head of Section

PRIORITY DOCUMENT
SUBMITTED OR TRANSMITTED IN
COMPLIANCE WITH RULE 17.1(a) OR (b)

Modtaget

20 OKT. 1999

PVS

NOVI

FORSKERPARK · INNOVATION · VENTURE

Patent- &Varemærkestyrelsen
Helgeshøj Allé 81
2630 Taastrup

Aalborg d. 18. oktober 1999

Vedr. **patentansøgning**

Hermed fremsendes en patentansøgning vedr. **signal processing**.

Opfinder: Anders la Cour-Harbo

Ansøger: NOVI Innovation A/S, Niels Jernes Vej 10, 9220 Aalborg Ø

Kvittering for modtagelsen bedes mærket **"signal processing"**

Med venlig hilsen

Hans Harding
Erhvervsforsker/Ph.D.

Direkte:
Tel : 9814 0938
Fax : 9814 0942
e-mail : hh@novi.dk

NOVI A/S
Niels Jernes Vej 10
Postboks 8330
DK-9220 Aalborg Øst
Danmark

Tlf. 96 35 45 00
Fax 96 35 45 99
Reg.nr. 166698
e-mail: novi@novi.dk

PA 1999 01503

Modtaget PD
2 0 OKT. 1999

19. oktober 1999

Anders la Cour-Harbo
c/o
Hans Harding
NOVI Innovation A/S
Niels Jernes Vej 10
9220 Aalborg Ø

Signal processing

A FAST AND ROBUST WAVELET TRANSFORM BASED ALGORITHM FOR ESTIMATING CHANNEL GAIN

A. la Cour-Harbo, J. Stoustrup

Aalborg University
Department of Control Engineering
Fredrik Bajersvej 7C, DK-9220 Aalborg, Denmark
alc@control.auc.dk, jakob@control.auc.dk

ABSTRACT

The measurement of channel gains is a widely used method for determining properties of substances. A common way of performing this measurement is by emitting a harmonic signal with known amplitude followed by a filtering of the received signal, which yields an estimation of the channel gain, and hence a quantification of an unknown substance property. These types of signals are unfortunately sensitive to various kinds of noise, making robust implementations difficult. The wavelet transform, being fast and highly adaptable, is proposed as a tool for making these estimation robust. This paper demonstrates that by combining a series of carefully designed signals and the versatility of the wavelet transform, it is possible, with low computational complexity, to make robust estimations of channel gains. The concern of this paper is measurement of channel gains, but the method might very well apply to other areas.

1. INTRODUCTION

One of the ways of determining the density, transparency or thickness of a substance or material, such as smoke, wine, glass, paper, plastic is channel gain measurements; by transmitting a signal with a known intensity through the substance or material, and estimating the resulting intensity, it is possible to determine the density, transparency or thickness. Channel gain measurements are also used for ascertaining the surface properties of, distance to, or mere presence of objects. In this case an emitted signal is reflected onto a receiver. An example is a system for automatically opening a door whenever a person is present in front of it.

1.1. The previous solutions

A typical way of making this type of measurements is emitting a simple signal, such as a harmonic signal, since this is easily constructed with analog electronics. Moreover the intensity of a harmonic signal is found by a plain band pass filtering. Alternatively a non-structured signal, like radiation or light with constant intensity, can be emitted. The estimation of the received intensity is in this case particularly simple. However, the use of simple signals makes the channel gain measurement sensitive to the environment, since most electrical apparatuses found in industry and at home emits (often unintentionally) all kinds of simple signals, both visually and audibly. For instance a remote control produces as series of infra red signal, while a television set emits a rather intense, high frequent sound. For every new application that utilizes channel gain measurements in this fashion it is therefore necessary with a great deal of testing and fine-tuning. A necessity which is both costly and time consuming.

1.2. The proposed solution

Since the simplicity of the signals is the Achilles' heel with respect to robustness of the estimations of the channel gain, a logical approach is to introduce more complex signals. That is signals carefully designed such that they are easily recognized even when overlaid with severe noise. Adaptive design of complex signals is most easily done digitally, and the proposed solution therefore assumes the possibility of digital signal processing. The key question then becomes what signal is best suited for transmission under the given conditions, including the overlaid noise, the characteristics of the electrical components, the properties of the transparent or reflecting material, and the capacity of the signal processor. The noise is a priori unknown, although in many applications some types of noise are likely to occur. Due to the low cost of the electrical components the characteristics of these can vary quite a lot, even for two seemingly identical components. The low cost priority also result in a fairly low signal processor capacity. In some applications the transparent or reflecting material is well-known, in others it is unknown. The large uncertainty on some of the main factors makes it virtually impossible to design 'the best' signal. For not only should the signal be immune to many types of noise, it is also subject to a trade off between recognizability (which often implies complexity), robustness, and processor capacity.

Instead of transmitting a simple signal, a signal designed to have certain properties are 'protected' by an inverse transform before transmission. The received signal is transformed resulting in the original signal overlaid with noise. Since the wavelet transform can produce predefined trade offs between time and frequency information, and since the design of the original signal is completely free, this method can be adapted to virtually any type of noise. Because the transform is linear, is energy preserving, and has perfect reconstruction, and because the original signal is known, it is easy to determine a number of properties of the current overlaid noise. This information can be used for automated, online adaptation. Good introductions to the wavelet theory are [10] and [9]. A more rigorous, mathematical treatment of the subject is given in [4].

This work is in part supported by the Danish Technical Science Foundation Grant no. 9701481

2. THE IDEA

A digital signal $\mathbf{s}_0$ is generated, processed and transmitted from emitter to receiver. The results is another signal $\mathbf{s}_r$, which is also processed to determine the intensity of transmitted signal, and hence the channel gain. The wavelet transform included in the processing is the discrete wavelet packet transform. The result of transforming, denoted by $\mathcal{W}(\cdot)$, is the representation of the signals in some basis, and the inverse transform, denoted $\widetilde{\mathcal{W}}(\cdot)$, is the reconstruction of the signal from whatever basis it is represented in.

The starting point is the signal $\mathbf{s}_0$, the structure of which eventually will determine the quality of the measurement, and from this the signal to be transmitted $\mathbf{s}_t$ is constructed by an inverse wavelet transform (from whatever basis the signal $\mathbf{s}_0$ is represented in) followed by an affine mapping to adjust it to the range of the emitter.

$$\mathbf{s}_t = \alpha\widetilde{\mathcal{W}}(\mathbf{s}_0) + \beta\mathbf{1}.$$

The transmission signal is given by $\mathbf{s}_r = T(\mathbf{s}_t)$, where T is the transfer function from emitter to receiver, including the characteristics of both components. T is assumed to be a constant transfer function, but the approach can easily be extended to handling dynamical ones as well. Assume that the transmission dampens the signal and adds noise, that is $T(\mathbf{x}) = G\mathbf{x} + \mathbf{e}_t$. Then the wavelet transform of the received signal becomes

$$\begin{aligned}\mathcal{W}(\mathbf{s}_r) &= \mathcal{W}(G(\alpha\widetilde{\mathcal{W}}(\mathbf{s}_0) + \beta\mathbf{1}) + \mathbf{e}_t) \\ &= G(\alpha\mathbf{s}_0 + \beta\mathcal{W}(\mathbf{1})) + \mathcal{W}(\mathbf{e}_t),\end{aligned}$$

where G is the channel gain. Since α and β are known this reduces to

$$\mathbf{s}_{wr} = G\mathbf{s}_n + \mathbf{e}_{wt}, \qquad (1)$$

where both $\mathbf{s}_r$ (hence also $\mathbf{s}_{wr}$) and $\mathbf{s}_n$ are known signals. This equation has three major degrees of freedom; the choice of original signal, the choice of wavelet transform, and the choice of solution method. The goal is a good estimation of the channel gain G, and by exploiting all three degrees of freedom this is possible even for severe noise conditions.

2.1. The wavelet transform

The wavelet transform has two purposes in this framework: Producing the emitted signal and transforming the noise contribution. The former is determinant for the energy consumption of the emitter, and for the emitters influence on the surroundings, while the latter has direct influence on the quality of the estimation of G. In this paper we will be concerned solely with the quality of the estimation.

The wavelet transform itself has a number of degrees of freedom, which can be exploited in the adaptation. Apart from the obvious choice of filter and choice of basis, the transform type is important; an integer-to-integer transform [1] might be attractive since the signals are digital (this would eliminate the quantization errors), the lifting technique [3, 8] could prove superior in adapting the transform to signal and/or noise, while a transform on finite fields [5] perhaps is the best solution to the dynamic range problem occurring in fixed point arithmetic. Another transform property is the handling of the ends of the signal. This is important since $\mathcal{W}$ is a wavelet packet transform, which by repeated transformations yields several elements, each with two ends. The 'ends' problem is traditionally dealt with either by periodization or by mirroring. Alternatively boundary filters [6] or time-varying transform [7] could be used to reduce the influence of the noise at the ends.

The choice of filter is usually be restricted to orthogonal filters, since non-orthogonal filters tend to have asymmetric frequency responses rendering the result of repeated transforms inhomogeneous with respect to gain in the various frequency bands. This property might be useful for suppressing noise, however, but this has, to the best of the authors' knowledge, not yet been investigated.

2.2. Solving the equation

The vector equation (1) can be considered as a system of n linear equations with $n + 1$ unknowns; some or all of the entries of the noise vector, and the gain. The size n of the system depends only on the number of non-vanishing coefficients in the original signal and the chosen basis representation (through $\mathcal{W}(\mathbf{1})$), and the coefficients on G is directly controllable via $\mathbf{s}_0$. This means that the linear equation system can be tailored to fit an approximate solution method such as least square. If the noise is normal distributed, $\mathbf{e}_t \sim N(\mu, \sigma^2)$, this will give the best result, independently of the wavelet transform. Inverse transforming (1) yields

$$\mathbf{s}_r = G\mathbf{s}_t + \mathbf{e}_t. \qquad (2)$$

Note that $\mathbf{s}_t$ can be any signal, and $\mathbf{s}_r$ is the result of the transmission. A least square approach could be formulated through a rewriting of (2) to

$$\|\mathbf{s}_r - G\mathbf{s}_t - \mu\mathbf{1}\|^2 = \sigma^2 N, \qquad (3)$$

where N is the length of the signal. Let σ be the smallest value for which (3) holds. Then (3) is an elliptic paraboloid with minimum in the (G, μ) plane. This minimum point is found when the G and μ discriminants are zero simultaneously. Solving that yields

$$G = \frac{\langle \mathbf{s}_r, \mathbf{s}_t\rangle - \mu\langle \mathbf{s}_t, \mathbf{1}\rangle}{\|\mathbf{s}_t\|^2} \qquad (4)$$

with

$$\mu = \frac{\langle \mathbf{s}_r, \mathbf{s}_t\rangle\langle \mathbf{s}_t, \mathbf{1}\rangle + \|\mathbf{s}_t\|^2\langle \mathbf{s}_r, \mathbf{1}\rangle}{\langle \mathbf{s}_t, \mathbf{1}\rangle^2 - N\|\mathbf{s}_t\|^2}. \qquad (5)$$

The smallest σ is then

$$\sigma^2 = \frac{\mu^2\langle \mathbf{s}_t, \mathbf{1}\rangle^2 - \langle \mathbf{s}_r, \mathbf{s}_t\rangle^2 + \|\mathbf{s}_t\|^2\|\mathbf{s}_r\|^2}{\|\mathbf{s}_t\|^2 N} - \mu^2 \qquad (6)$$

As long as the noise is normally distributed these estimations are fairly accurate. Unfortunately there is no way of immediately telling how accurate the estimation of G is.

Another way is to exploit two properties of the linear equations, namely that G is in all them and that the noise, although unknown sample by sample, has some approximately known properties (mean, energy, frequency distribution etc.). With the wavelet transform it is then possible to make the G estimation more robust than in the previous solution; having the freedom in choice of original signal, another possibility is to design the original signal such that $\langle \mathbf{e}_{wt}, \mathbf{s}_0\rangle$ is close to zero. Then

$$G = \frac{\langle \mathbf{s}_{wr}, \mathbf{s}_0\rangle}{\langle \mathbf{s}_n, \mathbf{s}_0\rangle} - \frac{\langle \mathbf{e}_{wt}, \mathbf{s}_0\rangle}{\langle \mathbf{s}_n, \mathbf{s}_0\rangle} \approx \frac{\langle \mathbf{s}_{wr}, \mathbf{s}_0\rangle}{\langle \mathbf{s}_n, \mathbf{s}_0\rangle}. \qquad (7)$$

If certain frequency bands in the noise are 'nice', i.e. has low mean square error or contains nearly white noise, the wavelet transform can target these intervals making, it easy to design a signal s_0 which has high probability of $\langle e_{wt}, s_0 \rangle$ being close to zero.

2.3. Verification of measurements

The special structure of the systems allows for solutions involving only easily calculated quantities, like the inner products. Such a simple approach, however, is sensitive to time localized noise, spikes in particular. To reveal occurrences of this type of noise the freedom in design of the original signal comes in handy. Let s_0 through s_K be $K+1$ signals with the properties

$$\langle s_k, s_m \rangle = 0 \quad \text{for } k \neq m \qquad \text{and} \qquad \langle s_k, e_{wt} \rangle \approx 0,$$

where e_t is a typical noise occurrences. When transmitting s_m the other K signals, called verifiers, can be used to indicate the quality of an estimation on the form (7). A time localized noise occurrence is still time localized in a wavelet transform, and $\langle s_{wr}, s_m \rangle$ could in such a case very well be a poor estimate of the gain. The inner products $\langle s_{wr}, s_k \rangle$ for $k \neq m$ would be similarly affected by the noise, independently of the channel gain. Comparing $\langle s_{wr}, s_m \rangle$ with each of the verifiers inner product with s_{wr} gives a quality of the estimation of G. A comparison could be done like

$$p = 1 - \exp\left(\frac{-BK \langle s_{wr}, s_m \rangle^2}{\sum_{k=0, k\neq m}^{K} \langle s_{wr}, s_k \rangle^2} \right), \tag{8}$$

where the exp is introduced to make the quality of the estimation absolute, that is $0 \leq p \leq 1$. Whenever the verifiers detect energy in the received signal (energy which then have to originate in noise), p becomes small. The higher the ratio of estimated gain and verifier energy, the closer p gets to 1, with B controlling how close. When some parts of the received signal is corrupted by noise, there might still be other usable parts. Then (7) and (8) can be restricted to these parts to give a G estimate unaffected by the corrupting noise.

3. RESULTS

A number of suggestions on how to utilize the wavelet transform to measure channel gain has been given in the previous section. The result of using a few of them in an infra red emitter-receiver implementation is presented in this section. In all cases the result of wavelet transforming with $\mathcal{W}$ is the fourth level in a wavelet packet transform decomposition. This level consists of eight elements, as indicated in the figures. The filter is Symlet 8 [2], and due to the short filter periodization is used. The noise is recorded with the infra red photodiode at 5 kHz, and the noise vector e_t is shown in figure 1c. As original signal a step function is chosen, figure 1a, and the function $x \mapsto 1000x + 2048$ is chosen as affine mapping. This mapping applied to s_0 is shown in figure 1b, which is then the emitted signal. The gain is known to be 0.00642. The received signal in shown in figure 1d, and the transform of this is shown in 1e.

Applying the least square approach (4)–(6) to the transmitted signal s_t, see figure 1b, and received signal, see figure 1d, gives a gain and mean which deviates only very little from the true values (see table 1). However, the addition of a single spike in the received signal (in this case 200 is added to sample 177) makes the estimation of G rather poor, and there is no immediate way of detecting this.

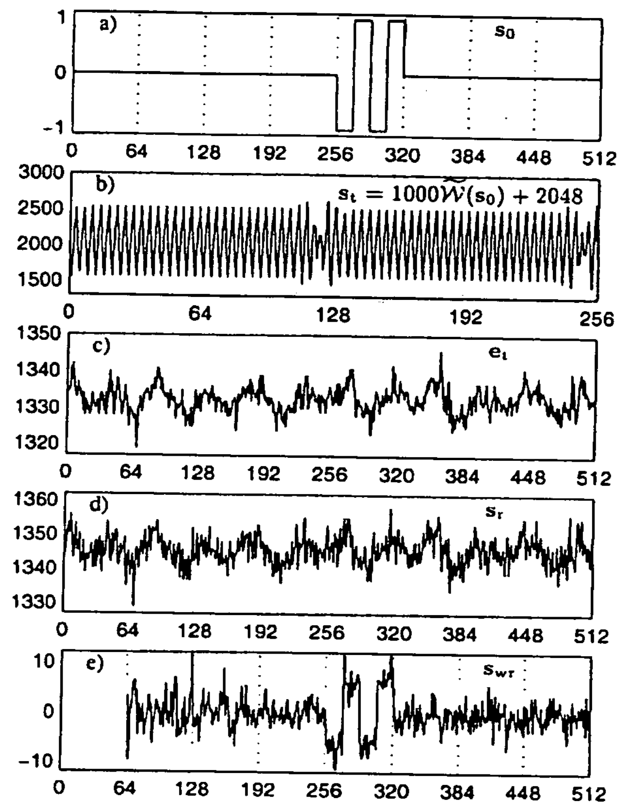

Figure 1: Experimental data from an infra red emitter–receiver implementation. a) original signal, b) emitted signal, c) transmission noise (experimental data), d) received signal, e) the received signal wavelet transformed.

The detection of a poor estimate is possible with the inner product approach (7). First, applying it to the wavelet transform of the received signal (figure 1e) yields a good estimation of G (see table 2). To determine the quality of the estimation two verifiers, s_1 and s_2 in figure 2a and b, are used. They have the same structure as s_0 while at the same time being orthogonal to s_0. The absolute quality measure p in (8) also shows a good estimation (B is chosen such that $p = 1 - \exp(-B \cdot 200) = 0.9$). When applied to the transform of the spiked, received signal (the same spike as before), the estimation is poor, which is easy to tell from the p

Description	Fig	$\Delta_{rel}G$	$\Delta_{rel}\mu$	$\Delta_{rel}\sigma^2$
No extra disturbance	1d	0.2%	0.03%	5%
Added 200 to sample 177	2d	23.3%	0.29%	171%

Table 1: Results of applying the least square methods (4)–(6). The three percentage columns shows the deviation between the estimated and the real values.

Description	Fig	$\Delta_{rel}G$	ϕ_0	ϕ_1	ϕ_2	p
No extra disturbance	1e	1.1%	416	2	29	99%
Spike at sample 177	2d	25%	512	112	149	16%
Interval [257; 288]	2d	47%	302	125	124	6%
Interval [289; 320]	2d	2.4%	210	13	19	85%
Interval [257; 272]	2d	2.7%	106	7	12	74%
Interval [273; 288]	2d	90%	196	118	112	3%
1st recursion, 1st method		7.7%	442	42	73	46%
2nd recursion, 1st method		1.5%	405	4	35	94%
1st recursion, 2nd method	2e	5.8%	435	21	52	75%
2nd recursion, 2nd method	2e	3.4%	425	9	40	91%

Table 2: Results of applying the solution method (7). The third column shows the deviation between the estimate and real value of G. Column four through six show the inner products $\phi_k = \langle s_k, s_{wr}\rangle$, and the last column the corresponding quality measure (8).

value. If the noise causing this poor estimated is localized in time (which the spike is) parts of the received signal can still be used for achieving a good estimate. Applying (7) and (8) to each half of the interval [257; 320], the p values reveal that the spike occurred in the first half of the received signal. At the same time a good estimation of G becomes available. Dividing the first half shows that the spike occurred in the second quarter of the received signal. This approach works equally well if the entire second quarter of the received signal has been corrupted.

If a number of spikes occur distributed along the entire received signal, the above method might fail. In this case a spike reduction method is useful. The estimated value of G (which for this spike example is off by 25%) indicates approximately the expected amplitude of the original signal in the transformed, received signal (via Gs_n). Any coefficients larger than this amplitude is most likely noise. The largest coefficient is then set to the expected value, which depends on the original signal, the so far estimated G, and the coefficient's place in time. The result of this approach is shown in table 2 (referred to as 1st method). When this large value 'neutralized', a better G can be estimated, and the next recursion 'neutralizes' the second largest value (there are two large values in the spike in figure 2c). Alternatively the alteration of the received signal can be done by a similar procedure before it is transformed. Instead of reducing one coefficient at the time, this reduced all 'too large' coefficients simultaneously. The effect of 1 and 2 recursions are shown in table 2 as 2nd method, and the graphical result in figure 2d.

4. CONCLUSION

The use of the wavelet transform for estimating channel gains is shown to be robust with respect to different types of noise. The versatility of the transform, including the choices of filters, bases, implementations etc., and the freedom in choice of original signal and verifiers makes the method highly adaptable. One particular use of the methods were presented through a infra red emitter–receiver example, but many other exploitations are possible. The low complexity and numerical stability of the discrete wavelet transform and the solution methods (mainly inner products) also makes this approach fast and suitable for low cost hardware implementation.

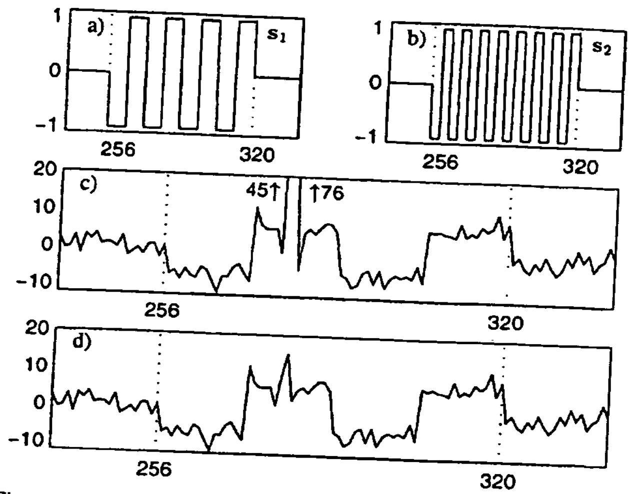

Figure 2: a) the first verifier, b) the second verifier, c) the received (spiked) signal wavelet transformed (the spike in the transformed signal consists of two large values 45 and 76), d) results of one and two recursions of 2nd method of spike reduction.

5. REFERENCES

[1] R. Calderbank, I. Daubechies, W. Sweldens, and B.-L. Yeo. Wavelet transforms that map integers to integers. *Appl. Comput. Harmon. Anal.*, 5(3):332–369, 1998.

[2] I. Daubechies. Orthonormal bases of compactly supported wavelets. II. Variation on a theme. *SIAM J. Math. Anal.*, 24(2):499–519, march 1993.

[3] I. Daubechies and W. Sweldens. Factoring wavelet transforms into lifting steps. *J. Fourier Anal. Appl.*, 4(3):245–267, 1998.

[4] Ingrid Daubechies. *Ten Lectures on Wavelets*. SIAM, 1992.

[5] F. Fekri, R. M. Mersereau, and R. W. Schafer. Theory of wavelet transform over finite fields. *Proceedings of IEEE ICASSP*, III:1213 – 1216, march 1999.

[6] C. Herley, Jelena Kovačević, K. Ramchandran, and M. Vetterli. Tilings of the time-frequency plane: Construction of arbitrary orthogonal bases and fast tiling algorithms. *IEEE Transactions on Signal Proccesing*, 41(12):3341 – 3359, december 1993.

[7] C. Herley and M. Vetterli. Orthogonal time-varying filter banks and wavelet packets. *IEEE Transactions on Signal Proccesing*, 42(10):2650 – 2663, october 1994.

[8] W. Sweldens. The lifting scheme: A construction of second generation wavelets. *SIAM J. Math. Anal.*, 29(2):511–546, 1997.

[9] M. Vetterli and Jelena Kovačević. *Wavelets and subband coding*. Prentice-Hall, 1995.

[10] Mladen Victor Wickerhauser. *Adapted Wavelet Analysis from Theory to Software*. A K Peters, May 1994.